Scenario Identification Process in Fuzzy Spatial Load Forecasting

Cláudio Monteiro
cmonteiro@inescn.pt

Vladimiro Miranda
vmiranda@inescn.pt

M. T. Ponce de Leão
mleao@inescn.pt

INESC Porto, Instituto de Engenharia de Sistemas e Computadores
and DEEC/FEUP, Faculdade de Engenharia da Universidade do Porto, Portugal

Abstract: In this paper we present a Spatial Load Forecasting (SLF) model based on Fuzzy Inference and Cellular Automata. The first part of the paper describes the Fuzzy SLF model, the training process, the implementation on a Geographical Information System (GIS) and the Fuzzy SLF functionality over a multiple time stages. In its second part the paper discuses the environment assessment for decision process by identifying scenarios resulting from geographical non-repetitive events.

Keywords: Spatial Load Forecasting, Geographic Information Systems, Fuzzy Inference, Cellular Automata, and Scenario Identification.

I. INTRODUCTION

Forecasting and Planning are complementary processes that can't be dissociated. Planners can use forecasts to predict and revise the outcome of alternative plans, and plans may be used to define the environment and events that influence the forecasts. In Distribution Planning one uses consumption forecasts that are a consequence of geographic influence factors, most of then resulting from urban plans. The urban plans are the basis to set non-repetitive events (e.g. building a road, land use directives, etc.) that define scenarios. The scenarios will represent several contrasting futures, identifying economic, technological, or event possibilities for the future.

There is also a relation, at the uncertainty structuring level, between forecasts and scenarios. Forecasts are strong statements about what will happen in the future when all relevant variables are taken into account. It is possible to structure uncertainties related with small deviations from a forecast statement. This kind of uncertainty modeling is presented in another paper [1]. Contrary to the approach of structuring uncertainties into forecasts, scenario planning requires the participation and responsibility of the Decision-Maker in the construction and evaluation of the scenarios, namely by running several forecasts. Scenario planning models multiple plans dependent on what the future should look like.

In this paper we will describe one expert system, implemented into a GIS for small area spatial load forecasting. In the second part of the paper we will discuss, and we illustrate with an example, the scenario planning approach for structuring uncertainties related with geographical events.

Land-use Spatial Load Forecasting (SLF) simulation methods have been largely used to model the process of the load growth in order to predict load evolution on a spatial and temporal basis [2]. The authors developed a SLF model joining the characteristics of Fuzzy Inference System and Cellular Automata [3]. The Fuzzy Inference model captures the geographical pattern of influence factors, estimating the potential for development, and cellular automata model the dynamics and spreading process over the geographical region, forecasting the development for consumer growth. The authors have further improved the model by transferring the dynamics of the forecasting model, from the Cellular Automata (CA) to the Fuzzy Inference Model [4]. In this last approach the saturation levels (consumer/km^2) of each consumer class are considered as input variables of the fuzzy system, and the CA model simulates only the consumer spreading over the geographical region. This temporal dynamics of Fuzzy SLF is controlled by a module (Scenario Coordinator), that defines for each stage the parameters and the geographical themes used in the simulation. The Scenario Coordinator allows the interaction with the planner for the identification of scenarios.

II. FUZZY SPATIAL LOAD FORECASTING

Spatial Load Forecasting (SLF) refers to models used to predict load growth in a region, based on the influence of several control factors, defined as “influence factors”. Examples of those factors are, for instance, the influence of a radial distance to an urban center or of the distance to a waste treatment center.

In recent years some works have enhanced the land-use methods applied to urban redevelopment, using fuzzy logic, GIS or multi-objective programming [5, 6, 7].

In urban planning, a large work is being done to model land-use conversion. This is done under the assumption that a simulation approach under the self-organizing paradigm is appropriate for addressing the process of land development [8, 9]. To simulate the dynamics of the process, a recent work adopts cellular automata (CA) - this approach emphasizes the way in which locally made decisions give rise to global patterns.

The authors developed Fuzzy SLF models, completely implemented in a GIS support. The kernel of the Fuzzy SLF is a set of rules storing a spatial and temporal behavior of consumption development. Selecting a set of geographical influence factors, the model is capable of capturing automatically the historical behavior of consumption growth or of allowing the direct specification of expert knowledge. The model can be applied to study other regions with a similar behavior by using the set of rules generated previously.

As shown in Figure 1, three main modules compose the Fuzzy SLF structure. The fuzzy system uses a set of

geographical influence factors to compute a continuous map of Potential-for-Development (PfD). The CA use these maps to simulate consumer growth over all the geographic region, which is the effective Development (D_t) at stage *t*. The third module is the scenario coordinator, responsible for the time coordination, looping the process throughout the stages of each scenario. The Scenario Coordinator is a table specifying the data to be used in each scenario. Some of these data may be acquired from the results of previous stages and other may by specified directly by the planners. For instance, the saturation levels are computed based on results from the previous stages, the influence factors may be geographical coverages specified by the planner and the parameters are constants necessary to calibrate the other modules.

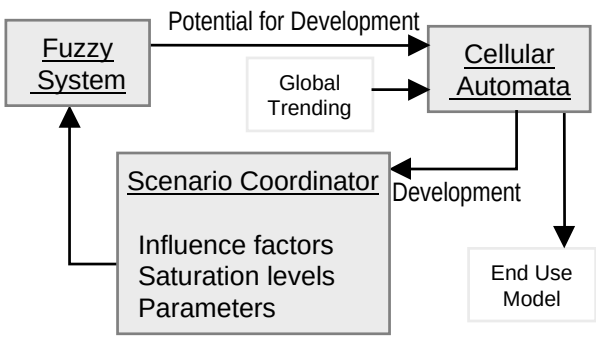

Figure 1 – Three kernel modules (Fuzzy System, Cellular Automata, and Scenario Coordinator) constitute the Fuzzy SLF model. This kernel must be coupled to other modules that can be designed independently.

The Fuzzy SLF is coupled to other two modules, the Global Trending and the End Use modules. These modules can be developed independently in different ways and will be not discussed here. The Global Trending forecasts, as output for each time stage, the total number of new consumers, of each class, that appear in the overall region. The End Use module describes the consumption of each consumer class, and uses the result of the Fuzzy SLF to estimate the electric power consumption growth.

III. SPATIAL FUZZY SYSTEM

The Spatial Fuzzy System is a GIS spatial model implementing a fuzzy inference engine similar to the fuzzy systems used in control theory [10].

The module described in this section uses a set of explanatory geographical variables, designated as spatial influence factors, to compute the PfD, for each specific consumer class.

Spatial influence factors to be considered in SLF are local factors, relative location factors, and neighborhood factors. The local factors are structural factors related with the site, and their effect is confined to the geographic cell unit (e.g. slope, altitude, and land use classification).

The distance to certain geographical features defines the relative location factors. For instance, proximity to roads, proximity to urban centers proximity to prohibitive areas or undesired proximity to certain facilities.

The neighborhood effect represents the influence of entities or features in an adjacent area or in its own geographic unit. Important neighborhood factors are the load saturation levels; these influence factor model the dynamics of the development change from stage to stage, influencing the results in the following time stages.

Each point in a map is associated with saturation curves S_i for each type *i* of consumer. A saturation curve describes the number of consumers of a given type, at a certain location, as a function of time. It usually displays an *S* shape curve (Figure 2). The derivative of this *S* curbs represent the PfD.

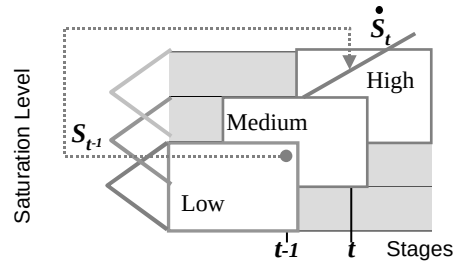

Figure 2 – The saturation curve *S* is represented in the fuzzy rules as a set of linguistic classifiers (low, medium, and high). The curve is built dynamically throughout the time stages. One of the Fuzzy System inputs is the saturation level and the output is the PfD.

In our approach, we do not define *a priori* any saturation curve. Instead, the shape of the saturation curve is built dynamically following the pattern implicit on thousands of fuzzy rules that compose the Fuzzy System.

The function that models the growth phenomena for each consumer class i could be represented by

$$\dot{S}_c\big|_t = f\left(S_1\big|_{t-1},...,S_c\big|_{t-1},I_1,...,I_i,...,I_p\right) \qquad (1)$$

where $\dot{S}_c$ represents the output of the model (*PfD* for consumer class c) and is the derivative of the saturation curve on stage *t*. The $S_c|_{t-1}$ represent saturation levels for each consumer class at stage *t-1* and the I_i represent other geographic influence factors.

A. Implementation on GIS

Many variants and operations can be used in fuzzy-logic inference [10]. This section will describe briefly the technique we implemented on a GIS; for more detailed information on fuzzy logic see references [11]. The Fuzzy SLF model is completely developed in the GIS language using the GIS spatial function to implement the fuzzy system.

A basic component of a fuzzy inference system is a fuzzy rule (see Figure 3). Rules are expressed using linguistic labels such as the rule: IF (road is close) AND (urban center is close) THEN (development growth index is 0.8). Fuzzy membership functions (MFs) associate linguistic labels (e.g. close) with a particular area of one of input or output variable. In our case, the THEN-part of each rule does not consist of a membership variable but of a crisp value 0.8. This is called a zero-order Sugeno fuzzy system. In an nth order Sugeno fuzzy system the THEN-part of each rule consists of a polynomial of degree n in the input variables.

Different shapes of MFs can be adopted such as triangular, trapezoidal, or Gaussian.

IF *(distance to road* is *CLOSE)* **AND**
(distance to urban centre is *MODERATE CLOSE)* **AND**
(terrain slope is *MODERATE)* **AND**
(domestic saturation (S_d) is *MEDIUM)* **AND**
(industrial saturation (S_i) is *LOW)* .
THEN
Domestic PfD is *20 consumers per stage per km^2* **AND**
Industrial PfD is *0.1 consumers per stage per km^2*

Figure 3 – Example of a fuzzy rule.

The inputs are maps computed by the basic GIS functions (e.g. distance functions, statistical or focal neighborhood functions, surface functions...). The intermediate operations done in the fuzzy system are specified in the set of rules stored in GIS lookup tables. These tables contain thousands of rules that are activated on specific regions of the maps. The activation is directly related with the activated linguistic label. Because several labels are activated at the same location (e.g. 0.3 close-to-road and 0.7 moderate-close), the combination of labels activates many rules in the same location, leading to computations with many maps in order to represent all the activations and the membership values.

After the definition of MFs we can formulate rules j in term of linguistic values. Input variables are combined in expressions using fuzzy operators such as fuzzy AND (T-norm) or fuzzy OR (T-conorm). In the case of a Gaussian MF, for a zero-order Sugeno fuzzy system, the fuzzy AND can be performed by the arithmetic product of membership values across the input variables x_v.

$$G_j(x_v) = \prod_v M_{iv}(x_v) \tag{2}$$

For each consumer class *c* the output value is calculated by the OR operation and can be generated by

$$O_c(x_v) = \sum_j w_j G_j(x_v) \tag{3}$$

where w_j is the THEN-part (or rule output weight) of the fuzzy rule *j*. Based on the multiple maps of rule activation and on the weight of each rule, stored in lookup tables, a continuous map of potential for development is computed, defined as PfD.

B. Training and tuning fuzzy system rules

The set of rules is meant to represent the function approximation $\dot{S}_c$. In order to capture the regression between geographic influence factors and potential for development, one must train the fuzzy inference model. In the scope of the present fuzzy inference model, training consists in finding the rule weights that better approximate the function $\dot{S}_c$. The training is based on a training data set composed by input/output vectors. The inputs are the geographical influence factors defined by the user as significant variables, in this case represented by maps (e.g. distance to roads, domestic saturation level, terrain slope, ...). The output is the historical development for a specific set of inputs, also represented as maps (e.g. consumer growth per year per square kilometer). Each vector corresponds to one pixel of a map and may be formally represented in the following way:

$$D = \left(\xi^k, \zeta^k\right),\ k = 1,...M,\ \xi^i \in \Re^n,\ \zeta \in \Re^m \tag{4}$$

These historical data could be used to perform training, where *M* is the number of training points, *n* is the number of influence factors and *m* is the number of consumer classes. This training would find the output weights that minimize the summed square error.

$$E = \frac{1}{2}\sum_{k=1}^{M}\left(O_k\left(\xi^k\right) - \zeta^k\right)^2 \tag{5}$$

Several methods can be used to train the fuzzy system, like the fuzzy relational model [12], the fuzzy basis function based model [13], and the neural-network-based fuzzy model [14].

If the IF-part of the fuzzy rules is fixed, the determination of weights w_j can be solved by the method of least squares based on standard matrix techniques

$$\begin{bmatrix} w_1 \\ \vdots \\ w_j \end{bmatrix} = \begin{bmatrix} \sum_k G_1(\xi^k)^2 & \cdots & \sum_k G_1(\xi^k)\cdot G_j(\xi^k) \\ \vdots & \ddots & \vdots \\ \sum_k G_j(\xi^k)\cdot G_1(\xi^k) & \cdots & \sum_k G_j(\xi^k)^2 \end{bmatrix}^{-1} \cdot \begin{bmatrix} \sum_k G_1(\xi^k)\cdot \zeta^k \\ \vdots \\ \sum_k G_j(\xi^k)\cdot \zeta^k \end{bmatrix} \tag{6}$$

When implemented on a GIS, the rules are coded as map regions. The number of rules activated in each geographical location is 2^v (the same number of maps is needed to store rule coding), where *v* is the number of input variables. For each rule map we compute a stack of maps with membership values $G_j(x_i)$.

These membership values are functions of the geographical value for the input variables (influence factors). All the calculations associated with each rule *j* are computed based on zonal functions available on the GIS, in which the zones are the regions where rules are activated.

The set of rules (variable labels, coding index and weights) is stored in a GIS database to be used on other time-space scenarios.

The maps of development potential thus obtained are continuous in space and static in time. To solve the SLF problem, which is discontinuous and dynamic, we use a cellular automata model.

IV. SPREADING WITH CELLULAR AUTOMATA

The CA theory was first introduced by Jon Von Neuman [15] and is ideally applied for dynamic discrete modeling [16]. A CA is a discrete dynamical system because space, time and system states are discrete and these states change sequentially over time and space. Each point in a rectangular spatial grid, called a cell, can have any one of a finite number of states. The states of the cells in the lattice are updated according to a local rule, which depends on the cell state and the state of its neighbors in the previous time step. The state of the entire lattice is updated synchronously in discrete time steps.

In our formulation, at any specific point of time t, the cellular automaton is a collection of binary states e_{ij}^{t} in cell location (i,j), with value 1 if a new consumer is added to the site and 0 if no consumer is added.

$$CA = \{e_{ij}^{t}\} \quad 0 < i \le r; \quad 0 < j \le c; \quad \forall e_{ij}^{t} \in E \tag{7}$$

where E is the finite set of states, r and c are the number of rows and columns of the map grid.

The CA is an iterative process, computing the development based on potential-for-development and calculating new potential based on the previous iteration development.

The Potential for Development (PfD) is initially set by the fuzzy system. The PfD is represented as a stack of continuous maps, one for each consumer type, representing the potential growth in number of consumers per stage and per geographic unit (e.g. 20 domestic consumers per stage and per km^2). The Development, which is the output of the CA, represents the effective number of consumer growth. A global geographical trending controls the global development, the sum of all developments in the region. The CA process finishes when the sum of all cell developments reaches the global trending value (e.g. the growth for year 2001 in the whole region tends to 250 industrial consumers and 5000 domestic consumers).

The iterative process of the CA is based on state transitions $S_i(t)$; in our model, these will be transitions from non-developed to developed. The state transition is done according to a set of rules such as

$$\text{if } P_i(t) > P_b(t) \text{ then } S_i(t) = 1 \text{ else } S_i(t) = 0 \tag{8}$$

In our model, a transition exists if the cell has a PfD value $P_i(t)$ higher than a specified boundary value $P_b(t)$. This value is specified by the system by ranking PfD intervals.

The development $D_i(t)$ is recalculated in each iteration incrementing the number of consumers, by steps D_{step} (measured in number of consumers), only on cells marked as developed, with $S_i(t)=1$.

$$D_i(t) = D_i(t-1) + S_i(t) \cdot D_{step} \tag{9}$$

The new potential $P_i(t+1)$ is recalculated based in three components:

- positive feedback of the cell on the previous iteration, weighted by α;
- neighborhood effect based on the 8 adjacent neighborhoods [17], weighted by β;
- innovation factor modeled as random noise, weighted by λ;

and is given at time $t+1$ by

$$P_i(t+1) = \alpha \cdot P_i'(t) + \beta \cdot \frac{1}{8} \cdot \sum_{j \subset \Omega_i} P_j'(t) + \lambda \cdot \varepsilon_i(t) \tag{10}$$

where α, β and λ are the weights for each component, with values [0,1] and $\alpha+\beta+\lambda=1$, and Ω is the set of adjacent neighbors cells. $P'_i(t)$ is the updated potential to development in time stage t on site i, computed based on the output of the fuzzy inference model $P_i(0)$ and on the development computed by the CA on iteration t:

$$P_i'(t) = P_i(0) - D_i(t) \tag{11}$$

At the end of each stage the PfD maps may be recalculated, using the fuzzy inference model and the new geographic data computed with the CA or introduced by the planner.

V. SCENARIO IDENTIFICATION PROCESS

The scenario identification process helps decision-makers to structure uncertainties identifying the events leading to different plans for the forecasting environment. Once these events identified, is necessary to verify correlations among them: this will eliminate many unrealistic scenarios resulting from the spatial and temporal combination of the events.

Because of their nature, simple forecasting models are incapable of modeling uncertainties by exploring the logic of how events occur. Scenario planning allows the decision-maker to define alternative environments for which decisions are taken.

A scenario identification process escapes to the rules of a systematic processing. The scenario must be identified by the planner, providing a consistent and coherent alternative for the possible futures. The Fuzzy SLF has a Scenario Coordinator module, which allows the planner to identify scenarios and to interact with the system along the several stages.

To help the identification of scenarios we may suggest the following three steps:

- Identify the uncertainty factors and events that influence the decision environment and analyze the logic between events.
- Develop scenarios that are consistent visions of the future. The alternative futures must be credibly co-ordinating events with very different outcomes.
- Ensure that events with identified uncertainty are critical for the decision. Due to the multiplicity of scenarios resulting from the spatial and temporal combination of events, it is important to limit our analysis only to the combinations of events that critically affect decisions and their performance.

In the Fuzzy SLF, most of the data are spatial data resulting from urban plans (road network, land use, etc.). The plans for urban development may result from the combination of the collaborative planning between several planning sectors as economic development, environment, utilities, etc.

VI. EXAMPLE

In this section the paper illustrates the application and results of the Fuzzy SLF and the scenario identification process. In this example we study the forecasting of domestic consumption in the island of Santiago in Cabo Verde (Africa). For each scenario we aim to forecast consumption growth along seven stages, which were defined for illustration purposes and cannot be seen as reflecting the actual situation in the region.

The geographical inputs (influence factors) considered are the following:

- Distance to main urban centers (4 linguistic labels)
- Distance to secondary urban centers (4 linguistic labels)
- Saturation Level (6 linguistic labels)
- Distance to roads (5 linguistic labels)
- Elevation (3 linguistic labels)
- Terrain slope (4 linguistic labels)

Linguistic labels associated with fuzzy membership functions reclassify the influence factor values (e.g. distance to roads between 0 and 2 km: VERY CLOSE; distance to roads between 1 and 3 km: MODERATE CLOSE).

The study region has 2400 km^2 including one main urban center and three secondary centers. The resolution on GIS spatial analysis was 250m which represents cell based maps with 38400 cells. The historical growth is based on the geographical building growth along the last 30 years. As training results we obtained 2500 rules completed with 146 rules defined by expert knowledge.

To identify the scenarios we first identified the factors that may affect the development.

We assume that the development of new urban centers is not credible; however, we admit that the areas defined as urban centers are related with saturation level. We do not consider these influence factors to identify scenarios, but in each stage we reclassify the urban centers and new distances to the centers will be recalculated.

In the same way, the saturation level is recalculated in each stage as a result of the Fuzzy SLF but this presents small differences and only a relative little influence in building multiple scenarios.

The influence factor "Distance to Roads" is an uncertainty factor especially adequate to formulate scenarios based on events. As for the construction of new roads, we admit the two possible events in this example: 1) constructing a new ring road around the main urban centre; 2) constructing a road along the south coast near the city. Once the location of the new features defined, one must define the timing of their construction. Because of insufficient economic resources only one of the events may happen in the first 6 stages.

The global trending, which is the forecasting target in each stage for the whole island, is another uncertainty factor that may be considered for identifying scenarios. Econometric analysis supplies us two possible global growth scenarios:

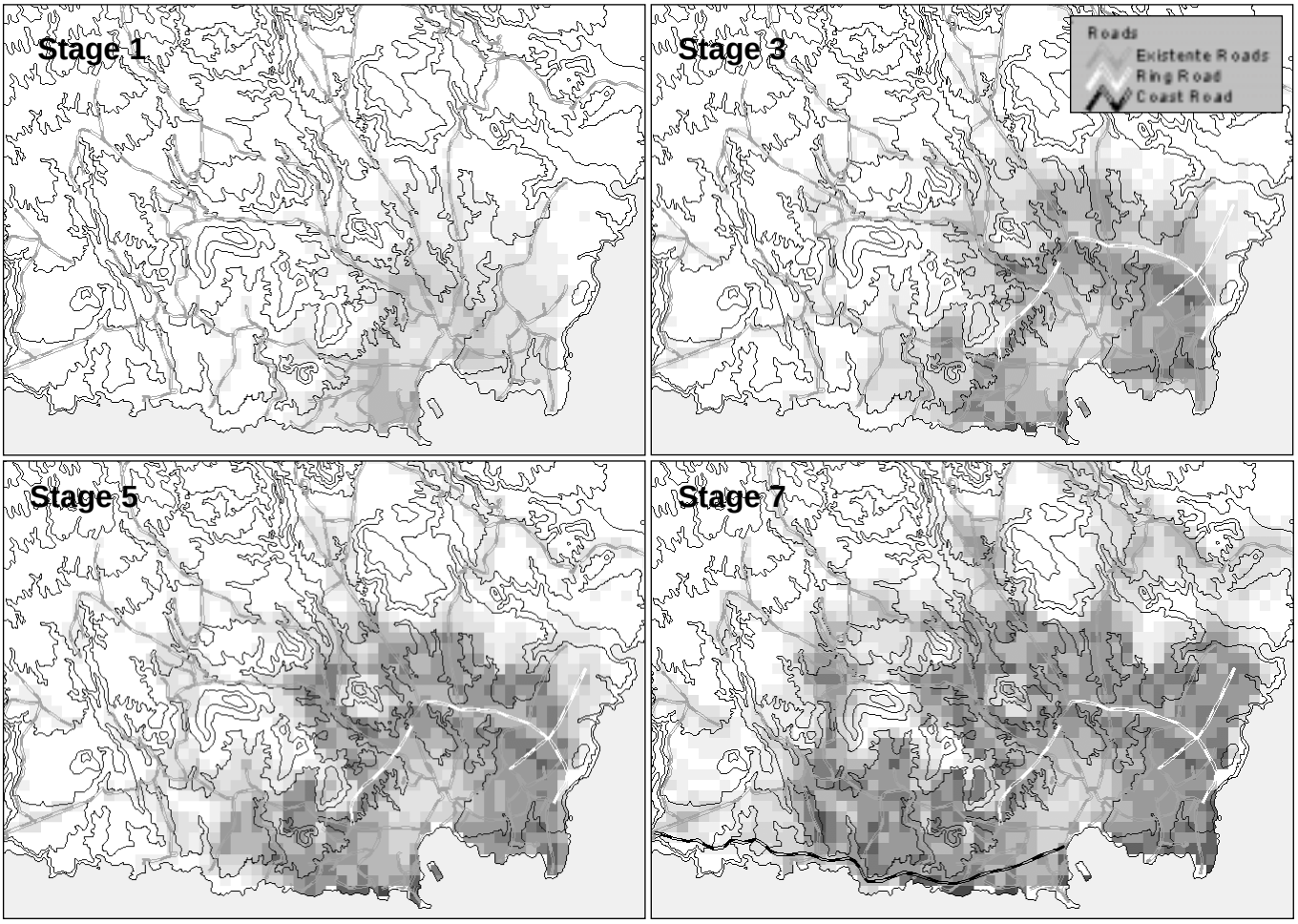

Figure 4 – Evolution of the number of consumers for scenario 2, along several stages. In this stage the Ring road was constructed on stage 2 and the coast road was constructed on stage 6.

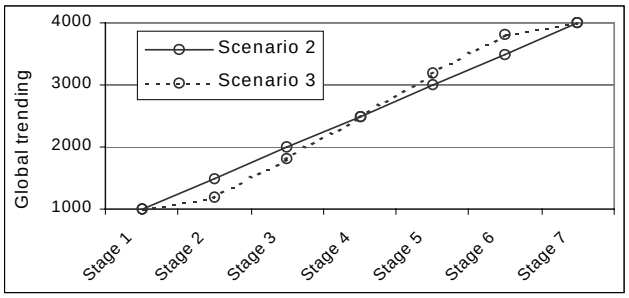

Figure 5 – Global trending used as input for scenarios 2 and 3.

1) scenario with gradual growth [1000, 1500, 2000, 2500, 3000, 3500, 4000]; 2) scenario with sigmoid growth [1000, 1200, 1800, 2500, 3200, 3800, 4000]. – see Figure 5.

Based on the referred events we identified several credible scenarios, for which we suspected of critical effect on decisions. In this work we identify, for illustration purposes, the following three scenarios:

Scenario 1

Global trending with gradual growth; coastal road built in stage 2; ring road built in stage 6

Scenario 2

Global trending with gradual growth; ring road built in stage 2; coastal road built in stage 6

Scenario 3

Global trending with sigmoid growth; ring road built in stage 2; coastal road built in stage 6

In Figure 4 we can observe the evolution of the growth of number of consumers for scenario 2, along the several stages. We didn't present images of the other two scenarios because the map results are too similar and undistinguishable for the quality of image presentation, possible in the paper.

We observed several differences on map results among the three scenarios. In order to analyze these differences we computed comparison maps between scenario 1 and scenario 2 and between scenario 2 and scenario 3. In both comparisons, the differences range between –10% and +10%. The comparison between scenarios 1 and scenario 2, related with spatial uncertainties for road construction, displays consequences on the spatial pattern for the development. On other hand, the comparison between scenario 2 and scenario 3, related with the global trending scenario, displays consequences on the magnitude of the development.

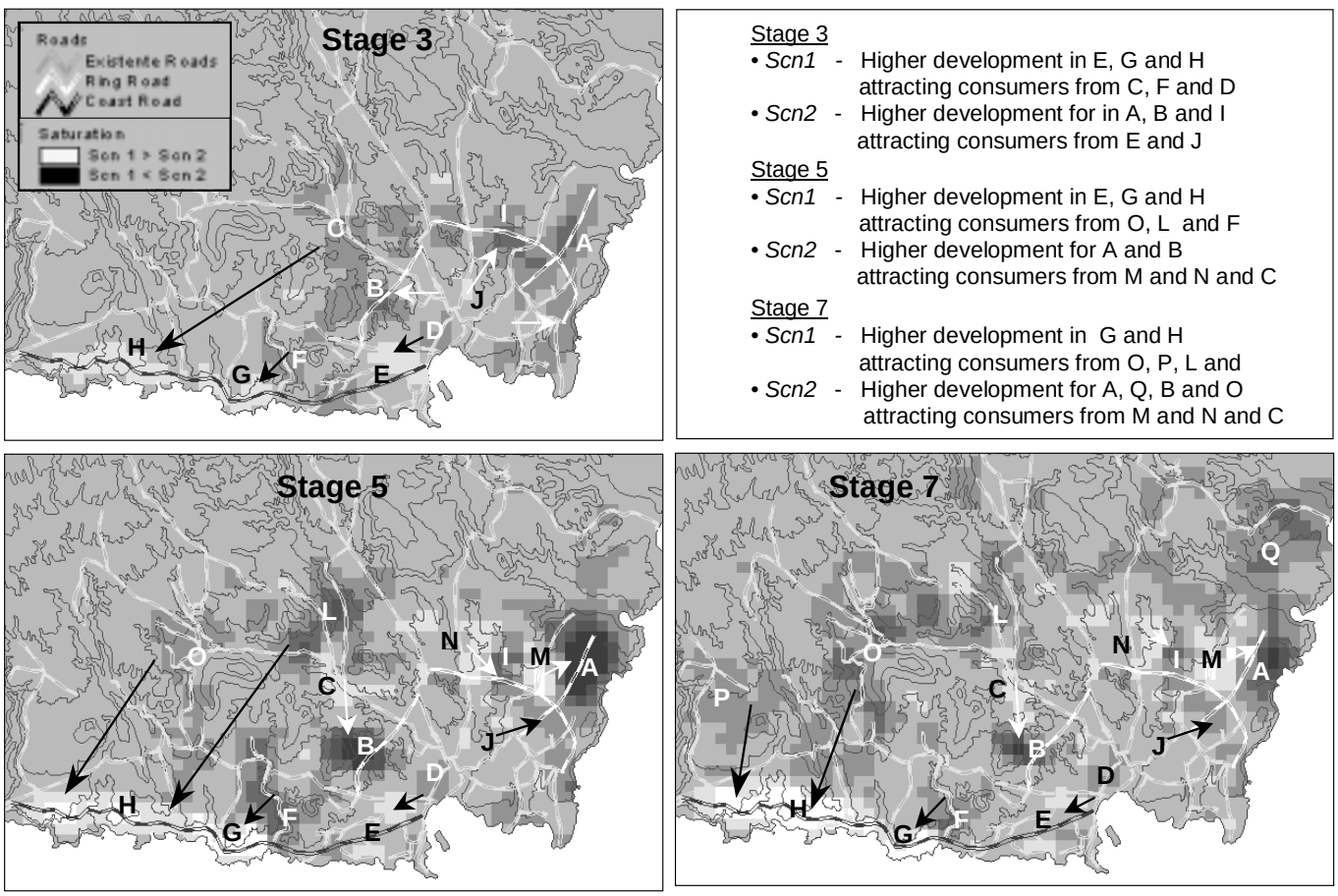

Figure 6 – Comparison maps between developments for scenario 1 (Scn1) and scenario 2 (Scn2). Dark zones represent locations with higher development for scenario 2 and light zones represent locations with higher development for scenario 1. The new roads constructed in each scenario become one attraction factor for development, displacing consumers from other zones. The white arrows represent the consumer displacement influenced by the "ring road" and the black arrows represent the displacement influenced by the "coastal road"

A. Comparing scenario 1 and scenario 2

To study the effects of the uncertainties resulting from spatial events (constructing new roads) we compare scenario 1 and scenario 2 by computing the spatial differences between maps of development. Scenario 1 represents the influence of constructing the "coastal road" and scenario 2 represents the influence of constructing the "ring road". At stage 6, both scenarios have the two roads built, but as we will see the different timings for constructing the roads will influence significantly the spatial patterns for future developments.

In Figure 6 we can observe these influences of the events of each scenario. In stage 3 the scenario 2 indicates higher development near the ring road, constructed in stage 2, but on sites quite far from the existent roads where the new road improves the accessibility (zones A, I and B). On scenario 1 the "coastal road" influences higher development in zones H and G. Note that zones C, F and D show development values higher for scenario 2 than for scenario 1. However this difference is not caused by any positive influence of the "ring road". The results are influenced by the negative effect of the coastal road, moving consumers from zones C, F and D to zones E, G and H. This effect is caused by the small elasticity of the global trending. If the development increases in a specific zone the fixed value for the global trending forces the decreasing in other zones with lower potential for development.

In stage 5 the zones near the "ring road" saturate and the adjacent areas with slower development (zones A and B) register the higher positive influence from the "ring road". It is interesting to observe that the increase in development in scenario 2 attenuates the natural development in zones C, N and M. For scenario 1, the coastal road continues to influence positively the development in zones G and H by displacing consumers from zones O, L and F.

On stage 7 we continue to observe the influence of the coastal road. However, due to the faster growth, near the "ring road" the positive influence is decreasing, fact observed on the lower intensity of zones A and B. It is interesting to observe the higher development in zone Q; the "ring road" doesn't influence directly this zone, but the higher development in the Northeast zone of the urban center, caused by the "ring road", influences positively the development in this area.

From this analysis we conclude that influences of discrete spatial and temporal events may originate very complex changes in the spatial load forecasting, and consequently the distribution planning. We also conclude that these events may affect drastically the directions for future development, especially when these events trigger the development on some regions changing the spatial pattern of the development.

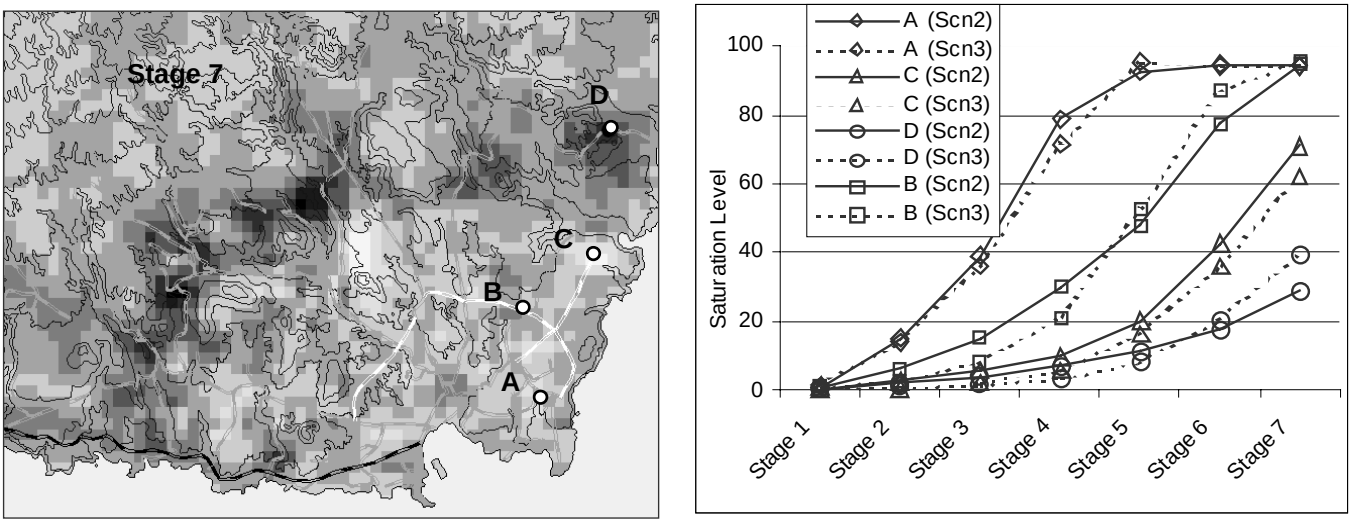

Figure 7 – a) map of saturation levels: comparison between scenario 2 and scenario 3, dark zones corresponding to areas where saturation in scenario 3 is higher than in scenario 2, and light zones corresponding to the inverse situation. b) chart representing, for the two scenarios, the saturation curves at 4 different points located on the map.

B. Comparing scenario 2 and scenario 3

The global trending differentiates scenario 2 and 3. In scenario 2 a uniform growth and in scenario 3 a sigmoid growth was used as illustrated on Figure 6.

The sum of the global trending along the 7 stages is the same for the two scenarios (175000 new consumers). The difference in the two scenarios is that on scenario 3 the global growth is more concentrated in the last three stages.

In order to compare the effects on the development caused by the two scenarios we analyze the differences in the saturation levels. The results from the comparison are presented on Figure 5. Due to the lack of space we only present a map on comparison for the last stage. By observing the several maps we concluded that higher global trending intensify the growth on areas with higher potential.

On Figure 7 we can observe a higher development, for scenario 3, represented by dark zones, on the areas of higher potential corresponding to stages 5 and 6.

The chart in Figure 7 shows the evolution of development in four different sites. The sites whit faster development are sited on areas close to the urban center A>B>C>D. We may

observe that in scenario 3 the saturation curves have a. relatively higher growth in last stages influenced by similar behavior of the global trending. However the effect of different global trendings is different in different places as observed by comparing curves C and D.

VII. CONCLUSION

In the first part of this paper a Fuzzy SLF model was presented, capable of capturing geographic behavior and expert knowledge and storing it as a set of fuzzy rules. The knowledge stored as rules may be applied in other time-space scenarios which similar consumer growth behavior. The model was designed to deal with spatial influence factors and was completely implemented into a Geographic Information System.

In Spatial Analysis many kinds of uncertainties exist and their effects may be very difficult to model. These uncertainties may be modeled as small deviations from the forecast result or may be a planning scenario. In this paper we discussed the scenario identification process. Most of the uncertainty inputs for Spatial Load Forecasting result from non-repetitive events and urban plans, these kinds of uncertainties must be structured as scenarios requiring the active participation of the Decision-Maker.

In the paper we explained the special ability of the Fuzzy SLF to structure these kinds of uncertainties by interaction with the Decision-Maker.

In a simple example of scenarios we observed the complexity of the SLF problem and the very different consequences resulting from quite different plans on urban planing and global demographic forecast. This proves beyond doubt how useful a process like Fuzzy SLF is, for Distribution Planning.

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